A FUZZY COOPERATIVE GENETIC ALGORITHM
FOR FUZZY MODELING

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To everyone who miss me while I'm working on this work

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ABSTRACT

Fuzzy modeling refers to the process of identifying the fuzzy parameters by defining fuzzy rules and fuzzy sets. The process of identifying the fuzzy parameters becomes complicated and difficult to evaluate particularly when it involves complex problems in engineering and medical applications. This is due to the fact that there are many fuzzy parameters to be identified such as the characteristics of the fuzzy rules and fuzzy sets. Besides that, the accuracy and the ability to interpret the fuzzy rules and the fuzzy sets would also need to be considered. This study proposes an improved method of fuzzy modeling called the Fuzzy Cooperative Genetic Algorithm (FCoGA) which integrates the Genetic Algorithm (GA) and Cooperative Coevolution Algorithm (CooCEA) that automatically generate and refine the fuzzy rules and the fuzzy sets. The GA is used to exploit the chromosomes that represent the fuzzy parameters whereas the CooCEA is applied to reduce the complexity of the fuzzy parameters representation which is carried out by subdividing chromosomes into three sub-chromosomes known as species. The FCoGA comprises of three phases which are simplification, tuning and evaluation. Simplification phase involves decomposition of the chromosomes into three species of chromosomes that represent the fuzzy parameters consisting of fuzzy rules, membership functions and length of the overlapping membership functions. The tuning phase involves the process of altering and tuning all the species. Lastly, the evaluation phase validates the performance of the FCoGA. Three benchmark datasets; breast cancer, diabetes and Iris have been used to evaluate the performance of the FCoGA. The experimental results showed that the FCoGA obtained the highest percentage of accuracy classification compared to other techniques such as conventional GA, multi-objective CooCEA, rule extraction and decision tree. The results also indicated that the FCoGA produced higher interpretability of a fuzzy model.

ABSTRAK

Permodelan kabur merujuk kepada proses mengenal pasti parameter kabur dengan memberi definisi terhadap peraturan-peraturan kabur dan set-set kabur. Terdapat beberapa masalah di dalam permodelan kabur apabila ia digunakan pada masalah yang kompleks di mana ia menyebabkan proses mengenal pasti parameter kabur menjadi rumit dan sukar untuk dinilai. Ini disebabkan proses mengenal pasti parameter kabur yang terlalu banyak seperti ciri-ciri peraturan-peraturan kabur dan set-set kabur. Selain itu, ketepatan dan kemampuan untuk mentafsir model kabur juga perlu diambil kira. Kajian ini mencadangkan satu kaedah automatik bagi permodelan kabur yang diberi nama Algoritma Genetik Kerjasama Kabur (FCoGA) yang menggabungkan Algoritma Genetik (GA) dan Algoritma Evolusi yang Bekerjasama (CooCEA) di mana ia dapat menjana dan memperbaiki peraturan-peraturan kabur dan set-set kabur secara automatik. GA menggunakan kromosom untuk mewakilkan parameter kabur manakala CooCEA digunakan untuk meringkaskan perwakilan penyelesaian yang terlalu kompleks dengan memecahkan kromosom kepada tiga sub-kromosom yang dikenali sebagai spesies. Terdapat tiga fasa utama di dalam FCoGA iaitu memudahkan, mengubah, dan menilai. Fasa memudahkan adalah proses pemecahan kromosom kepada tiga spesies yang mewakili parameter kabur; peraturan kabur, fungsi keahlian dan panjang pertindihan fungsi keahlian. Fasa mengubah melibatkan proses mengubah dan memperbaiki semua spesies. Akhir sekali, fasa menilai pula ialah proses penilaian prestasi FCoGA. Di dalam proses menilai, tiga piawaian set data iaitu barah payudara, diabetis dan bunga telah digunakan. Hasil analisis menunjukkan bahawa FCoGA dapat mencapai ketepatan pengelasan yang tinggi berbanding dengan kaedah-kaedah lain di dalam permodelan kabur seperti GA yang biasa, CooCEA yang mempunyai banyak objektif, pencabutan peraturan dan pokok keputusan. Di samping itu, FCoGA berupaya untuk menjana model kabur yang mudah untuk difahami.

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LIST OF ABBREVIATIONS

ANN	–	Artificial Neural Networks
AR	–	Auto-Regressive
BNN	–	Biological neural networks
BOA	–	Bisector of Area
CEA	–	Coevolutionary Algorithm
COG	–	Center of Gravity
ComCEA	–	Competitive Coevolutionary Algorithm
CooCEA	–	Cooperative Coevolution Algorithm
DB	–	Data Base
EA	–	Evolutionary Algorithm
EP	–	Evolutionary Programming
ES	–	Evolutionary Strategy
FCoGA	–	Fuzzy Cooperative Genetic Algorithm
GA	–	Genetic Algorithm
GFRBS	–	Genetic Fuzzy Rules Base System
GFS	–	Genetic Fuzzy System
GP	–	Genetic Programming
IDE	–	Integrated Development Environment
KB	–	Knowledge Base
MOM	–	Mean of Maxima
NIC	–	Network Interface Card
NN	–	Neural Network

PID	–	Pima Indian Diabetes
RAM	–	Random Access Memory
RB	–	Rule Base
SFE	–	Sozonov Fuzzy Engine
SOFRGP	–	Self-Organized Fuzzy Rule Generation Procedure
UCI	–	University of California, Irvine
WBCD	–	Breast Cancer Diagnosis

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CHAPTER 1

INTRODUCTION

1.1 Background

In many decision-making environments, there are several factors that need to be considered in order to ensure the optimum solution can be achieved. Sometimes, the factors that are to be taken into consideration are unknown and uncertain. This situation happened due to the lack of expert knowledge or the absence of expertise (Stephanou and Sage, 1987; Negnevitsky, 2002). In acquiring the expert knowledge, it involves many knowledge-processing procedures. The knowledge from many different experts needs to be collected and organized. In addition, it is vital to formalize the knowledge before applying it to the problem. However, acquiring the expert knowledge is costly and the process of collecting the knowledge is time consuming. Dealing with this situation, using an expert system is a good choice. An expert system is a computer program that is built with the expert knowledge in order to solve a specific problem. There are two approaches in obtaining the knowledge which are the knowledge derived from the experts or by extracting the knowledge from available data. As the process of acquiring the experts' knowledge is time consuming and costly, to obtain the expertise's knowledge also involves many procedures. On the other hand, the process of extracting the knowledge from the data is more efficient in terms of the lesser cost and shortens the time of performing it. Through data collection, a scientist can extract and interpret knowledge in the data in order to determine the pattern of the data, to find out the parameter that contains in the data and their relationship, to predict the physical and environment of the nature, and also to make a better decision based on the knowledge contained in the data. It works through the process of learning, extracting and presenting the knowledge in the form that is acceptable by human. However, several issues will arise when the data is inaccurate and incomplete which can result the knowledge to be imprecise, uncertain, or unreliable. Due to that, the fuzzy system is seen as a good choice to deal with these issues where it is used to represent and highlight the knowledge that is imprecise, uncertain and unreliable (Tsipouras *et al.*, 2008; Gadaras and Mikhailov, 2009).

Fuzzy system works by implementing the fuzzy logic and approximate reasoning, as well as incorporating the expert knowledge in the inference system in order to obtain the desired output from the system input values (Wang, 1997). In developing the fuzzy system, fuzzy parameters are needed to be identified in order to obtain the desired behavior of the system. This process is known as the fuzzy modeling (Reyes and Sipper, 2002; Cordon *et al.*, 2004). Fuzzy system works well on simple problems, but when applied on complex problems like engineering (Pulkkinen *et al.*, 2008; Mendonca *et al.*, 2009; Wang *et al.*, 2009) or medical problems (Ghazavi and Liao, 2008; Stylios *et al.*, 2008; Gadaras and Mikhailov, 2009), the construction of the fuzzy system becomes complicated. This might be due to the identification of many fuzzy parameters. Due to that, a method is needed for identifying the fuzzy parameters where an automatic process to identifying the fuzzy parameters is performed.

The following section will describe the challenges that arise in the fuzzy modeling in details followed by a review about the statement of the problems of this study. Next, the objectives of this study are presented. Lastly, the significance and scope of the study are discussed.

1.2 Challenges in Fuzzy Modeling

The process of building the fuzzy system is a hard process, especially for real-problems. This is because of the identifying process of the parameters that is crucial where it has influences on the performance of the system (Chen *et al.*, 2007; Zong-Yi *et al.*, 2008; Gadaras and Mikhailov, 2009). Generally, the fuzzy parameter that needs to be identified is the fuzzy model which refers to a collection of fuzzy rules and fuzzy sets. Before the fuzzy model is identified, several factors need to be considered. For the fuzzy rules, the factors are the number of rules, the antecedent and consequence, and the linguistic variable and the linguistic value. For the fuzzy set, the factors are the number of membership function, the types of membership function and the shape of membership function. These factors need to be considered in order to produce the fuzzy rules and fuzzy sets with more accurate and more interpretable. Furthermore, it turns out to be difficult because of the computation grows exponentially together with the increase of the number of variables in the system especially for the real world problems. This problem is known as the *curse of dimensionality* which is a major problem in the development of the fuzzy system (Reyes and Sipper, 2002). Therefore, this problem becomes the first challenge in this study. In dealing with this problem, an automatic approach in the fuzzy modeling is proposed.

There are many techniques that can be applied to automate the fuzzy modeling. Current trend shows that Evolutionary Algorithm (EA) is the most popular technique that is being used, especially the Genetic Algorithm (GA: Kim and Ryu, 2005; Kelesoglu, 2007; Dimitriou *et al.*, 2008; Li *et al.*, 2008; Evsukoff *et al.*, 2009; Li and Wang, 2009). Most of the works combine a fuzzy system with GA because of the good learning capabilities offered in solving problems. GA can be viewed as a search technique where the goal is to find the exact or approximate solution for the optimization problems. GA performs well in optimization problems, but when it is applied in complex problems such as when many dimensions of data (Luukka, 2009), when the value of data in a big range (Hong *et al.*, 2008; Alcala-Fdez *et al.*, 2009), when the search space is large (Li and Wang, 2009), involve multi-classification problem (Har-Peled*et al.*, 2002; Brinker*et al.*, 2006) and involve many parameters setting (Lau *et al.*, 2009), it tends to stuck in the local optima and thus performs poorly (Wang, 1997). With complex problem, it requires high computation power due to the representation of the solution. This happened due to the identification of many factors of fuzzy parameter such as the number of fuzzy parameters and their characteristics, where it makes the representation of the solution become complex. As a result, this might have contributed to the loss of the interpretability of the fuzzy model where the fuzzy model maybe becomes unreliable and uncertain. In addition, to evaluate the solution, time is very consuming. Therefore, there is a need to embody a method to simplify the representation of the solution in the interest of avoiding the fuzzy model to lose its interpretability. Derived from this situation, another challenge in the fuzzy modeling is to employ a decomposition method, which is the Cooperative Coevoutionary Algorithm (CooCEA) into GA (Potter and Jong, 2000; Reyes and Sipper, 2002; Xing *et al.*, 2007; Yang *et al.*, 2008; Zhu and Guan, 2008; Xing *et al.*, 2009). By implementing this technique, it is hoped that the CooCEA can reduce the complexity of the representation of the solution in order to improve the interpretability of the model.

1.3 Statement of the Problem

In fuzzy modeling, the identification of the parameters in the fuzzy system is essential for its operation. These parameters affect the performance of the system. Therefore, it is become a problem in fuzzy modeling because several factors must be considered in order to develop the fuzzy system. These factors are the accuracy of the results and interpretability of the fuzzy model (Xing *et al.*, 2007; Evsukoff *et al.*, 2009). These factors become important issues in the fuzzy modeling because it needs to deal with these factors at the same time. As a consequence, it is a difficult process to design a method of the fuzzy modeling in dealing with the accuracy and interpretability at the same time. Moreover, the extraction of the knowledge in the data can be difficult if the data is limited, complex, inaccurate and incomplete (Yang *et al.*, 2008; Fernandez *et al.*, 2009).This is the second problem in the fuzzy modeling which can make the knowledge obtained to be imprecise, wrong or simply uncertain (Tsipouras *et al.*, 2008; Gadaras and Mikhailov, 2009). Therefore, there is a need for a technique where it can automatically adjust, alter and fine-tune the knowledge in order to assure the specific requirement achieved. Besides that, a major problem in the fuzzy modeling is the *curse of dimensionality*. This happened due to the demand in the identification process of the many fuzzy parameters when it is applied on large search space and complex systems (Reyes and Sipper, 2002). The problems in fuzzy modeling can be summarized as follows:

(i) An automated approach in fuzzy modeling is needed to automatically alter, adjust and tune the fuzzy parameters.

(ii) Identification of many factors of fuzzy parameters such as number of fuzzy model and its characteristic.

(iii) Constraint of the data when data is limited, complex, inaccurate and incomplete.

1.4 Objectives of the Study

The main goal of this study is to develop a method that can automatically generate the ‘best’ of the fuzzy models that took into account the accuracy and interpretability of the model, and can achieve a better result when it is applied on the classification data. For that specific purpose, the following objectives need to be accomplished:

(i) To develop an algorithm named Fuzzy Cooperative Genetic Algorithm (FCoGA) for fuzzy modeling by incorporating GA with the CooCEA.

(ii) To generate fuzzy model that has a higher interpretability by using the CooCEA that decomposed the representation of the solution (cooperative chromosome) into sub-solutions (species).

(iii) To propose fuzzy modeling method that is able to achieve a higher accuracy of the classification by introducing two levels of fitness evaluation which are at the species level and cooperative chromosome level.

1.5 Scope of the Study

In this study, three datasets are used, particularly the Iris dataset, Pima Indian Diabetes (PID) dataset and Wisconsin Breast Cancer Diagnosis (WBCD) dataset. These datasets are obtained from the UCI machine learning repository. The scopes of the proposed method are as follows:

(i) The scope of the proposed method is focusing on the classification.

(ii) Use GA and CooCEA to randomly generate the initial population into three species that represented the fuzzy parameters where the fuzzy parameters are fuzzy rules, fuzzy sets and the length overlap in fuzzy sets.

(iii) In the interest of evaluating the performance of the proposed method, *k*-fold cross validation method is used and the accuracy is calculated to measure its performance.

(iv) Use three benchmark datasets in experiments where these dataset obtain from University of California, Irvine (UCI) machine learning repository which are the cancer dataset, diabetes dataset and flower dataset.

(v) In order to measure the performance of the proposed method, it will be compared with several works in the fuzzy modeling.

1.6 Significance of the Study

Fuzzy modeling can be viewed as a grey-box modeling because it allows the modeler to extract and interpret the knowledge that is contained in the data and also to imbue it with a prior knowledge (Babuska and Verbruggen, 1996; Reyes and Sipper, 2002). It is difficult to apply the fuzzy system on complex problems due to the requirement of the system. This is because the representation of the solution becomes more complex and difficult to understand by the human knowledge. Because of that, this study applies learning and tuning capabilities of GA, and decomposes method that is inspired by the CooCEA. With the learning and tuning capabilities of GA, the process of altering and adjusting the fuzzy model can be performed automatically. Meanwhile, the CooCEA is able to decompose the component in fuzzy model into sub-components thus can reduce the complexity of the representation of the solution. Therefore, the significance of this study is to create a method that automate the fuzzy modeling where the generation process of the fuzzy model can be performed automatically, and produce a fuzzy model that took into account the accuracy and interpretability of the model. As a consequence, it can help and facilitate computer scientists to produce computer expert systems such as the application to detect the breast cancer in patients.

1.7 Structure of the Thesis

This thesis is organized into six chapters. General content descriptions of subsequent chapters in this thesis are given as follows:

(i) Chapter 1 describes the background of the study, challenges in the fuzzy modeling, statement of the problem, objectives, significance and scope of the study.

(ii) Chapter 2 reviews the domain of this study which includes the review of the fuzzy system, the fuzzy modeling, approaches of fuzzy modeling and the advance methods in the fuzzy modeling.

(iii) Chapter 3 begins with the review of the research activity. Following that is the discussion of the proposed method and the review of the benchmark datasets involved. Besides that, the experimental environment is also discussed.

(iv) Chapter 4 describes the steps involved in the proposed method. This includes the representation of the cooperative chromosome, fitness evaluation and the reproduction process.

(v) Chapter 5 discusses the experimental result, discussion and analysis of the proposed method. First and foremost, the results of the experiments are presented. Then it is followed by the discussion section which elaborates the contributions of this study and finally the analysis of the proposed method.

(vi) Chapter 6 concludes the study and presents the contributions. The future works of the study are also discussed.

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